

# How to build a brain

## Linear Transformations



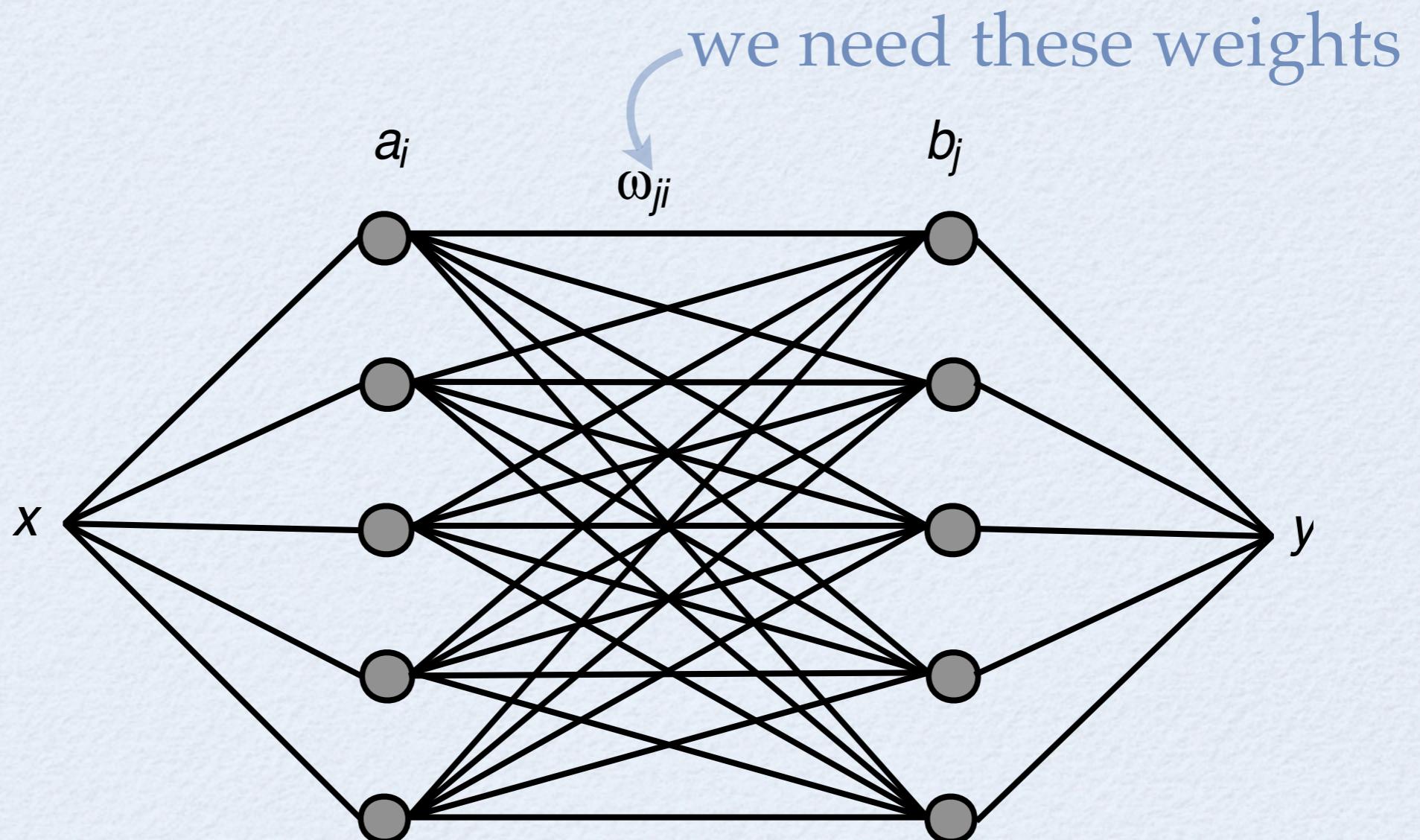
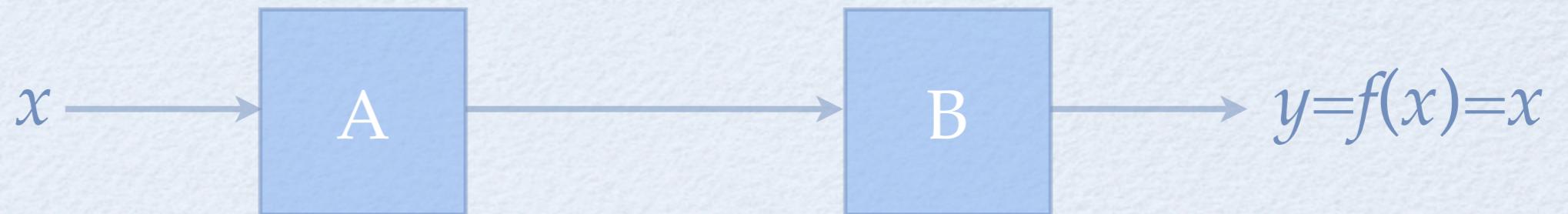
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# Principle 2: Transformation



encoding	$\sum_n \delta_i(t - t_n) = G_i(\mathbf{e}_i \cdot \mathbf{x}(t))$	( spikes from neuron $i$ at time $t_n$ )	( signal, $\mathbf{x}(t)$ )
decoding	$\hat{f}(\mathbf{x}) = \sum_{i,n} h_i(t - t_n) \phi_i^{f(\mathbf{x})}$	neuron model generating spikes	
		preferred direction vector	$f(\mathbf{x}) = 2\mathbf{x}$
		stimulus signal	
		computed function of stimulus	
'B' neuron	$h_i(t - t_n)$	PSCs convolved with spikes	
	$\phi_i^{f(\mathbf{x})}$	optimal linear weights for $f(\mathbf{x})$	

# A communication channel



# Connection weights

- Define the representations of both pops:

$$\begin{aligned} a_i(x) &= G_i [J_i(x)] & b_j(y) &= G_j [J_j(y)] \\ &= G_i \left[ \alpha_i \tilde{\phi}_i x + J_i^{bias} \right] & &= G_j \left[ \alpha_j \tilde{\phi}_j y + J_j^{bias} \right] \\ \hat{x} &= \sum_i a_i(x) \phi_i^x & \hat{y} &= \sum_j b_j(y) \phi_j^y \end{aligned}$$

- Define the computation:  $y=f(x)=x$
- Substitute our estimate of  $x$  into  $b$  repn

NB:  $\mathbf{e}$  and  $\tilde{\phi}$  are the same!

# Connection weights

- Substituting:  $y = x \approx \hat{x}$

$$\begin{aligned} b_j(x) &= G_j \left[ \alpha_j \tilde{\phi}_j x + J_j^{bias} \right] \\ &= G_j \left[ \alpha_j \tilde{\phi}_j \sum_i a_i(x) \phi_i^x + J_j^{bias} \right] \\ &= G_j \left[ \sum_i \omega_{ji} a_i(x) + J_j^{bias} \right] \end{aligned}$$

$$\omega_{ji} = \alpha_j \tilde{\phi}_j \phi_i^x$$

# With spikes\*

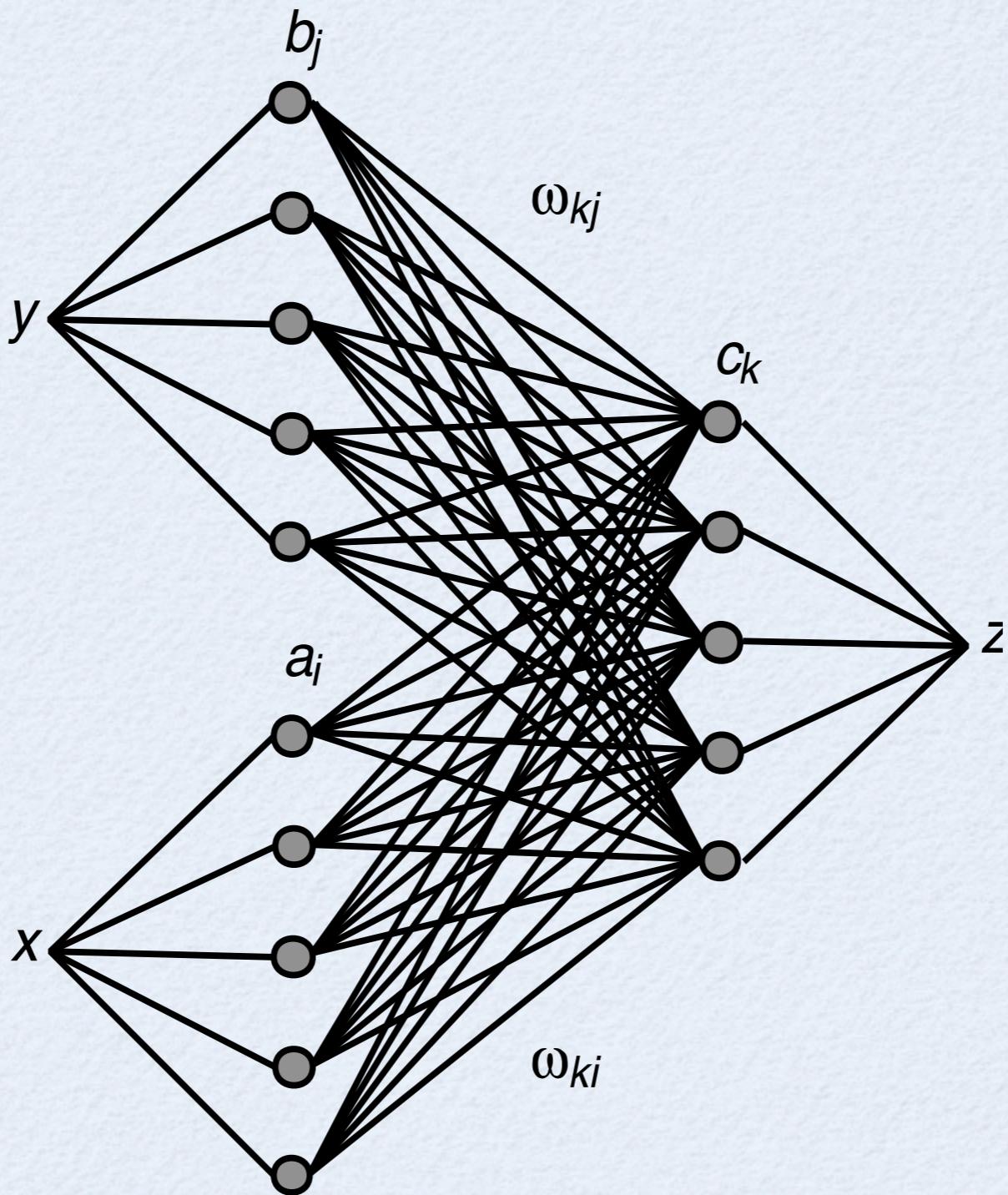
- Write the spiking estimate

$$\begin{aligned}\hat{x}(t) &= \sum_i a_i(x(t)) \phi_i^x \\ &= \sum_{i,n} h_i(t - t_{in}) \phi_i^x\end{aligned}$$

- Then do the same substitution:

$$\begin{aligned}b_j(x(t)) &= G_j \left[ \alpha_j \tilde{\phi}_j x(t) + J_j^{bias} \right] \\ &= G_j \left[ \alpha_j \tilde{\phi}_j \sum_{i,n} h_i(t - t_{in}) \phi_i^x + J_j^{bias} \right] \\ &= G_j \left[ \sum_{i,n} \omega_{ji} h_i(t - t_{in}) + J_j^{bias} \right]\end{aligned}$$

# Adding scalars



# Doing the math

- Volunteer?

$$\begin{aligned} c_k(x + y) &= G_k \left[ \alpha_k \tilde{\phi}_k(x + y) + J_k^{bias} \right] \\ &= G_k \left[ \alpha_k \tilde{\phi}_k \left( \sum_i a_i(x) \phi_i^x + \sum_j b_j(y) \phi_j^y \right) + J_k^{bias} \right] \\ &= G_k \left[ \sum_i \omega_{ki} a_i(x) + \sum_j \omega_{kj} b_j(y) + J_k^{bias} \right] \end{aligned}$$

$$\omega_{ki} = \alpha_k \tilde{\phi}_k \phi_i^x \quad \omega_{kj} = \alpha_k \tilde{\phi}_k \phi_j^y$$

# Recipe for linear trans.\*

- 1. Define the repn (enc/dec) for all variables involved in the operation.
- 2. Write the transformation in terms of these variables.
- 3. Write the transformation using the decoding expressions for all variables except the output variable.
- 4. Substitute this expression into the encoding expression of the output variable.

# Vectors

- Nothing new. Representation:

$$\begin{aligned} a_i(\mathbf{x}) &= G_i \left[ \alpha_i \left\langle \tilde{\phi}_i \mathbf{x} \right\rangle_m + J_i^{bias} \right] \\ \hat{\mathbf{x}} &= \sum_i a_i(\mathbf{x}) \phi_i^{\mathbf{x}} \end{aligned}$$

- Transformation

$$\mathbf{z} = C_1 \mathbf{x} + C_2 \mathbf{y}$$

# Vectors

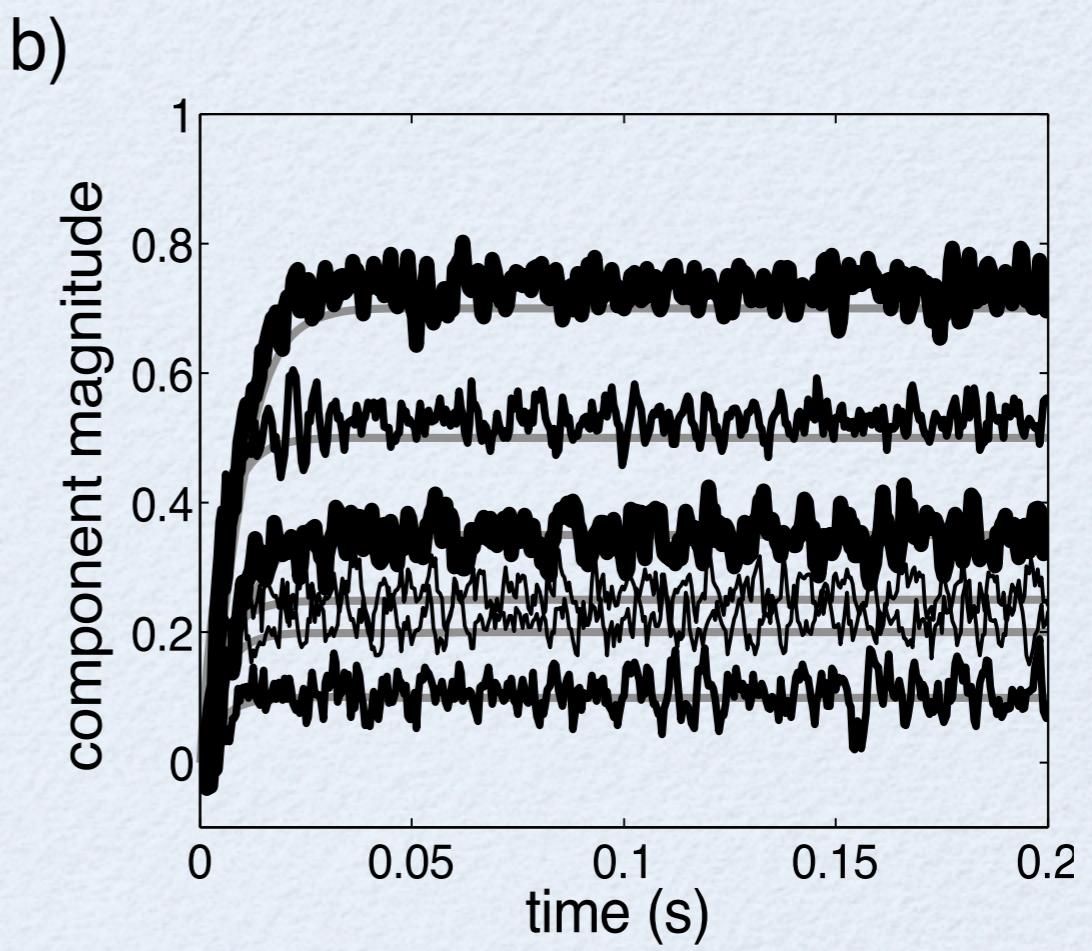
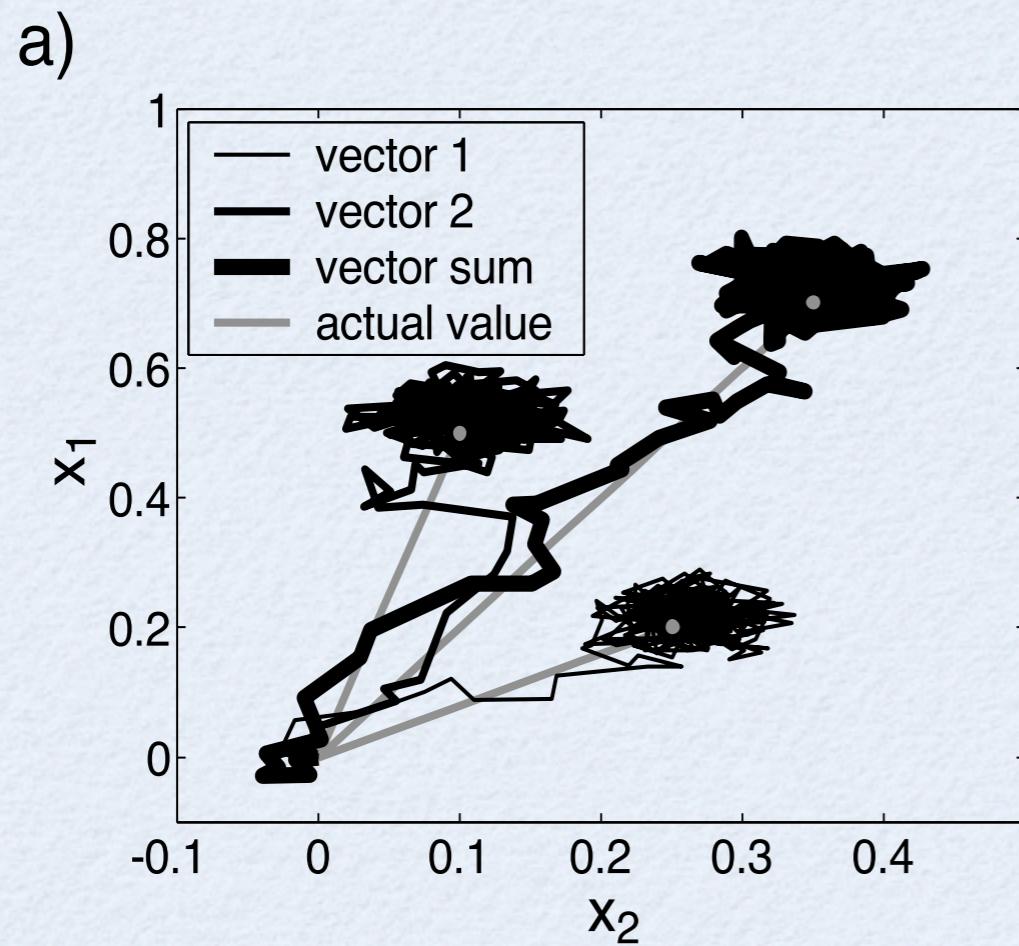
- Substitution

$$\begin{aligned} c_k(C_1\mathbf{x} + C_2\mathbf{y}) &= G_k \left[ \alpha_k \left\langle \tilde{\phi}_k(C_1\mathbf{x} + C_2\mathbf{y}) \right\rangle_m + J_k^{bias} \right] \\ &= G_k \left[ \alpha_k \left\langle \tilde{\phi}_k \left( C_1 \sum_i a_i(\mathbf{x}) \phi_i^{\mathbf{x}} + C_2 \sum_j b_j(\mathbf{y}) \phi_j^{\mathbf{y}} \right) \right\rangle_m + J_k^{bias} \right] \\ &= G_k \left[ \sum_i \omega_{ki} a_i(\mathbf{x}) + \sum_j \omega_{kj} b_j(\mathbf{y}) + J_k^{bias} \right] \end{aligned}$$

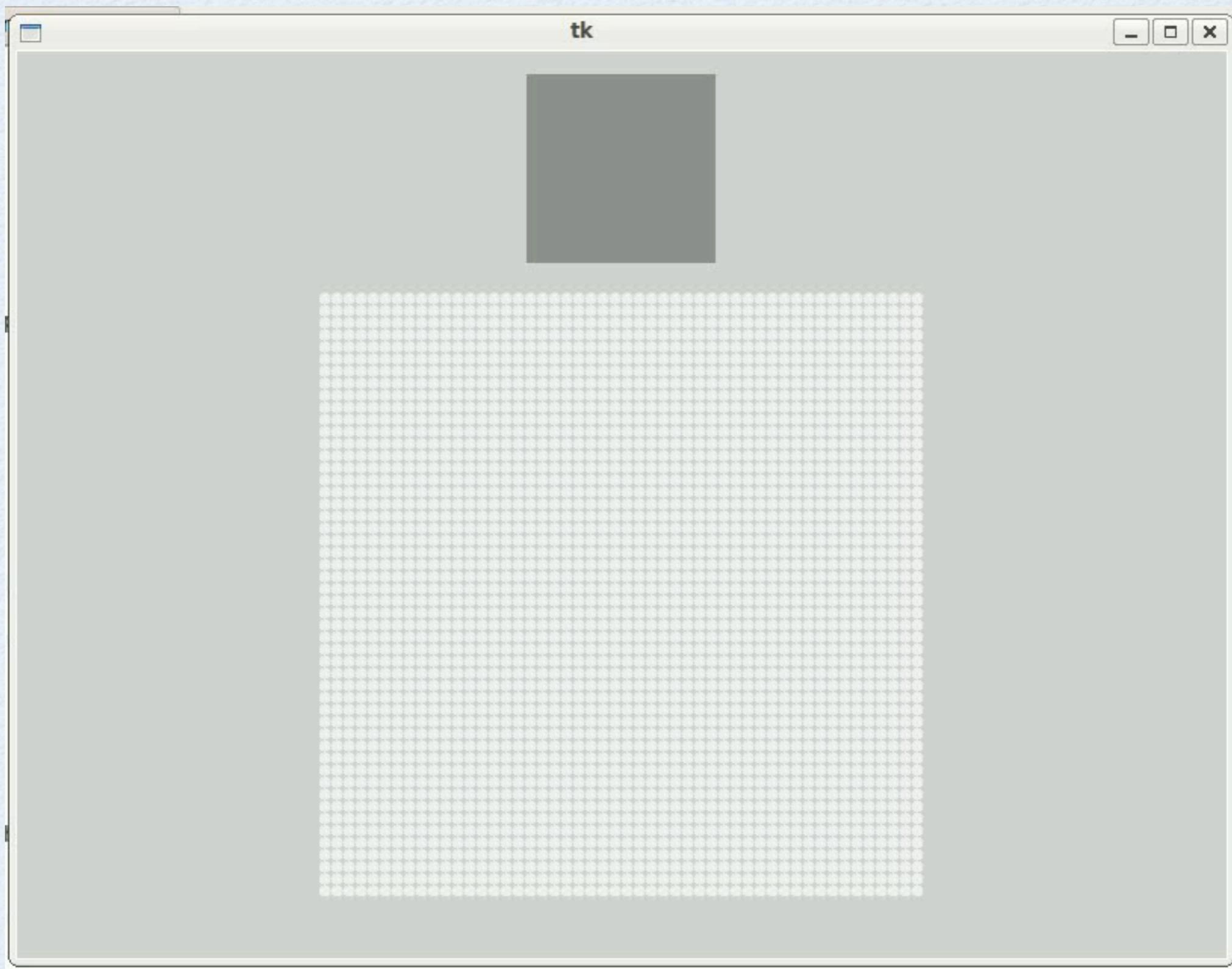
$$\omega_{ki} = \alpha_k C_1 \left\langle \tilde{\phi}_k \phi_i^{\mathbf{x}} \right\rangle_m \quad \omega_{kj} = \alpha_k C_2 \left\langle \tilde{\phi}_k \phi_j^{\mathbf{y}} \right\rangle_m$$

# Vector addition

- a) vector space; b) components



# 25D Vector Representation



# Representational hierarchy\*

<i>Kind</i>	<i>Encoder</i> ( $a_i(x)$ )	<i>Decoder</i> ( $\hat{x}$ )
Scalar (1)	$G_i [\alpha_i x + J_i^{bias}]$	$\sum_i a_i(x) \phi_i$
Vector ( $N$ )	$G_i [\alpha_i \langle \tilde{\phi}_i[n] x[n] \rangle_n + J_i^{bias}]$	$\sum_i a_i(x[n]) \phi_i[n]$
Function ( $\infty$ )	$G_i [\alpha_i \langle \tilde{\phi}_i(\nu) x(\nu) \rangle_\nu + J_i^{bias}]$	$\sum_i a_i(x(\nu)) \phi_i(\nu)$
Vector Field ( $\infty \times N$ )	$G_i [\alpha_i \langle \tilde{\phi}_i(\nu, [n]) x(\nu, [n]) \rangle + J_i^{bias}]$	$\sum_i a_i(x(\nu, [n])) \phi_i(\nu, [n])$